Green Inventions: Is Wait-and-see a Reasonable Option?*

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Abstract. We analyze the potential of different knowledge stocks to decrease the technological gap between the leader in green technology inventions and its followers in order to identify if wait-and-see is a reasonable option to benefit from knowledge. Our econometric results indicate that it is difficult to decrease the technological gap and remain competitive in the generation of green technologies without timely accumulating green knowledge. Although effects from external green knowledge stocks also contribute to decrease the technological gap, the effects are moderate and they cannot compensate the lack of internal green competences. Non-green knowledge stocks even tend to increase the technological gap.

Keywords: Innovation; knowledge; patents; environment; technological change; spillovers

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Executive summary

This paper analyses how difficult it is to close the gap to the technological leader and test whether a wait-and-see strategy is a reasonable option to remain competitive in the green technological market. More concretely the paper analyzes the impact of different knowledge stocks on the gap to the green technological leader on the basis of a broad industry level data set.

The econometric estimations and a number of robustness tests considering, e.g., policy effects, suggests that, firstly, internal green knowledge is more important than external green knowledge in order to decrease the gap to the technological leader. Although available green knowledge from other industries within a country contributes to diminish the gap to the leader, it can only marginally compensate the lack of internal green knowledge. Hence, the spillovers from internal sources of green knowledge seem to be much larger than the spillovers from external sources. Secondly, internal green knowledge is more important than (internal and external) non-green knowledge in order to decrease the gap to the technological leader. This result contradicts the widely shared view that a strong knowledge base in *non-green* technologies reduces the risk of permanently lagging behind, since it is assumed that the technological distance between green and non-green inventions is low, and consequently firms can switch into green invention activities in case markets are developed. Instead, our results show that internal non-green knowledge does not reduce the technological gap and external non-green knowledge even increases the gap to the green technological leader. Looking at the disaggregated level of green technological areas we even observe gap increasing effects of internal non-green knowledge for some areas.

Consequently, we can show that a wait-and-see strategy does not seem to be a promising way to proceed if one wants to face the environmental challenges and to be at (or close to) the technological frontier and thus keeping alive the options to benefit economically from future markets for green technologies. Hence, timely investments in the development of green inventions seem to be necessary.

1 Introduction

Environmental friendly technological innovations are necessary in order to address climate change. Only with significant technological developments of both existing low-carbon technologies and new ones, climate change can be efficiently addressed (see IPCC 2014). However, due to the 'double externality problem'[1], markets alone are unlikely to provide sufficient incentives for firms to develop such technologies. And indeed, recent studies at the firm and industry level have shown that green innovations currently are less profitable, i.e. they show lower returns, than non-green innovations (see Marin 2014, Soltmann et al. 2014). In case that "green" markets develop and the profitability of green technologies will increase, it could thus be an option to wait and to delay considerable investments in green invention activities. However, such a wait-and-see strategy can cause high costs of permanently lagging behind technologically or even miss the opportunity to enter the market before the gap to the technological leader gets too large.

The success of a wait-and-see strategy strongly depends on how "freely" available knowledge can be used to close the gap to the technological leader. Firstly, the success of such a strategy depends on the relative importance of the inventors' own (internal) green knowledge vs. external green knowledge for closing the gap. If external green knowledge is of relatively high importance, it is indicated that such knowledge can be transferred and copied easily and incorporated successfully into the green invention activities. Hence, a wait-and-see strategy may be beneficial. Secondly, it depends also on the relative importance of internal non-green knowledge vs. internal green knowledge for closing the gap to the technological leader. If internal non-green knowledge

[1] Firstly, due to the public goods nature of knowledge (see, e.g., Geroski 1995, Popp 2011) and due to financial market imperfections green technology investment decisions are complex and often linked with financial constraints. Secondly, because the greatest benefits from green innovation are likely to be public rather than private, the customers' willingness to pay for these innovations is low (see, e.g., Beise and Rennings 2005, Faber and Frenken 2009, Hall and Helmers 2013).

is of relatively high importance, then a firm may also continue to invest in its less risky traditional non-green invention activities and opt for a wait-and-see strategy in terms of green inventions. For instance, chemistry and material science may be as important as research on energy and the environment for the development of green technologies (OECD 2011a). Accordingly it may be easier to technologically catch up in the green sector, if one has already a well-developed traditional knowledge base and it may make sense to invest now in currently more profitable non-green technologies.

In the paper at hand we analyze the impact of different knowledge stocks on the gap to the green[2] technological leader on the basis of a broad industry level data set. We distinguish between the focal industry's internal and external (home country and foreign countries) knowledge stocks, and stocks of green and non-green knowledge, respectively.

In order to define the gap to the technological leader we follow the approach of Verspagen (1991).[3] He identified the technological gap as the difference between the logarithm of the knowledge of the focal entity and the logarithm of the knowledge of the leading entity (see Griffith et al. 2004 for a similar definition based on total factor productivity). Based on econometric regressions we then analyze the relationship between this "gap" variable and the different knowledge stocks.

So far, the impact of different knowledge stocks on the gap to the green technological leader has not been investigated. However, there are some studies that analyze the impact of different

[2] Patent documents considered as green inventions are identified according to the OECD Indicator of Environmental Technologies (see OECD 2012). Since we look at patent families we prefer to talk about inventions rather than innovations. See data section for more details on these issues.

[3] We do not apply a stochastic frontier approach (Green 2005b, Battese and Coelli 1992), since it is likely that firms with considerable green inventions have a relatively lower productivity level compared to firms without or with fewer green inventions. In this case such an approach does not make sense, since a greater distance to the frontier might be related to larger green invention activities. See section about the empirical framework for further explanations.

knowledge stocks on current green innovation activities. Most related to the investigation at hand is the study of Aghion et al. (2015) that is based on firm level data for the auto industry.[4] They distinguish between green and non-green knowledge stocks, when analyzing their impact on current green innovation activities. Although their main focus is on politically induced innovation, their results allow some conclusions about the impact of available knowledge on green patent applications for the specific industry.

The study at hand complements the existing literature in several respects. Firstly, we investigate the effect of the knowledge stocks on the gap to the green technological leader and not only on the level of green innovations, which is crucial in order to make a prediction on wait-and-see opportunities. Secondly, our study is based on industry level (panel) patent data and aims to provide a general and balanced view across industries and countries. This is of particular importance for policy makers, since the effects of environmental policies are not limited to a single industry. Moreover the use of aggregated patent data has several beneficial features. (A) it allows us to use the OECD Stan database to control for other than knowledge factors that are likely to be related to current invention activities. (B) empirical analyses at the industry level are not effected by firm specific technological (patent) cycles which could distort the analyses. (C) it allows us to generate a data set on inventions that covers the whole manufacturing sector (22 two and three digit industries, respectively), the most important countries of green invention (13 OECD countries that are responsible for 95% of all green patents and total patents worldwide), and a period of 30 years. Thus, we are able to consider a broad set of knowledge pools and to draw conclusions about their

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[4] Moreover, Verdolini and Galeotti (2011) analyze the impact of internal and external knowledge in energy technologies. Popp (2006) analyzes the relationship between the relevant knowledge stock in foreign countries and technological activities in the US and vice versa. Popp et al. (2011) analyze the impact of global knowledge on the investment in wind, solar photovoltaic, geothermal, and electricity from biomass and waste. These studies do not distinguish between green (internal, external) and non-green (internal, external) knowledge stocks and they do not focus on the “technological gap”.

relative importance in order to reduce the gap to the green technological leader. Furthermore, the balanced data set enables us to control for correlated unobserved heterogeneity between the industries of the different countries.

The econometric estimations and a number of robustness tests considering, e.g., policy effects, show that the magnitude of the internal green knowledge stock is the key factor in order to reduce the gap between the technological leader and its followers. Although positive and significant spillovers from green knowledge accumulation outside the industry can be detected, their marginal effect to decrease the technological gap is only half the size compared to the accumulated internal green knowledge. Moreover, the magnitude of non-green knowledge stocks even tend to significantly increase the gap, indicating that path dependency of innovation activities play an important role, i.e. that the costs of switching between green and non-green invention activities are considerable. Consequently, we can show that a wait-and-see strategy does not seem to be a promising way to proceed if one wants to face the environmental challenges and to be at (or close to) the technological frontier and thus keeping alive the options to benefit economically from future markets for green technologies. Hence, timely investments in the development of green inventions seem to be necessary.

2 Conceptual background and hypotheses

2.1 Sources of available knowledge

There are different pools of knowledge that may have an effect on an industry's gap to the green technological leader. In line with Mancusi (2008) we distinguish between internal knowledge and external knowledge. *Internal knowledge* refers to the focal industry's knowledge stock. We distinguish two types of external knowledge, namely the knowledge accumulated in the focal industry's home country in other industries (*country knowledge*) and knowledge accumulated in the focal entity's industry in foreign countries (*foreign knowledge*).[5] As our analysis focus on green technologies and not on innovations in general, the available pools of knowledge can furthermore be separated in green-specific knowledge pools and pools related to non-green knowledge. Thus, we define a total of six different pools of knowledge. The aim of this paper is to identify the impact of these knowledge pools on the gap to the green technological leader.

2.2 Impact of available knowledge

To the best of our knowledge the effect of different knowledge pools on the gap to the technological leader has not been analyzed so far. However, there is some literature that analyzes the impact of different knowledge pools for the current level of innovation activities. As the gap to the technological leader is directly related to the industries' innovation activities, it is likely that the predictions for the level of innovation activities also hold for the gap to the technological leader, i.e. if a knowledge pool is expected to positively affect the current level of innovation activities, it is likely that it also reduces the industry's gap to the technological leader.[6] In order to formulate

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[5] Knowledge accumulated in other industries in foreign countries (*foreign inter-industry knowledge*) is a further pool of knowledge that may affect a focal industry's current green invention activities. However, due to multicollinearity with the *country knowledge*, i.e. the home inter-industry knowledge, it is not possible to separately identify the effects of foreign inter-industry and foreign (intra-industry) knowledge given the available number of observations. We focus on intra-industry knowledge. This decision is supported by the results of previous empirical studies that find significantly stronger effects for foreign intra-industry knowledge than for foreign inter-industry knowledge on current invention activities (see Malerba et al. 2013, Mancusi 2008). Malerba et al. (2013) even find that the total effect of foreign knowledge is almost explained by its intra-sectoral component.

[6] This assumption implies that the different knowledge pools primarily affect the focal industry's internal green invention activities but not the green invention activities of the technological leader. As the internal knowledge pools and the knowledge pools in the focal industry's home country (country pool), respectively, should be more relevant for the focal industry rather than the technological leader located in another country, we expect that the assumption at least holds for these two types of knowledge. The assumption, however, is more problematic for the industry pool that refers to an industry's accumulated knowledge in all other countries. As this knowledge pool is not restricted to a

our hypotheses, we thus directly refer to the literature that analyzes the effect of different knowledge pools for current innovation activities.

There are two main channels through which available knowledge affects current innovation activities. Firstly, available knowledge is expected to stimulate current innovation as it serves as a source of information. We will call this effect the ‘spillover effect’. As we distinguish two different types of technologies, this ‘spillover effect’ may either come from green knowledge or come from traditional non-green knowledge.

However, in contrast to the spillover literature (e.g. Blundell et al. 1995, Crepon et al. 1998) that analyzes the impact of general knowledge for current innovation, we do not only distinguish between different knowledge pools (internal, external) referring to the same technology, but also between knowledge pools of different technologies, i.e. we distinguish between green and non-green knowledge pools. And that is where a second channel comes in. From previous literature (e.g. David 1985, Utterback 1996) we know that accumulated knowledge related to a specific type of technology does not only serve as an important basis to further develop this technology, but also reduces a firm’s/industry’s flexibility to switch between technologies. Accordingly, available knowledge within either green or non-green technologies also represents opportunity costs, making a switch to other technologies less likely. We call this second effect ‘path dependency effect’.

As the path dependency effect can be negative, the net effect, i.e. the combined effect of the spillover and path dependency effect, of a certain knowledge pool on the gap to the technological leader may even be negative. Such a negative effect can hardly be explained by the spillover literature alone. In what follows, we will discuss the two effects in more detail.

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specific country, it should not only affect a focal industry’s invention activities, but also the invention activities of the industry’s technological leader. If the industry pools would more directly affect the technological leader than the focal industry, the effects would go in the opposite direction from what we expect.

Spillover effect

Knowledge is a semi-public good (non-rival and non-excludable), since not all results from knowledge production activities are appropriable. At least some of the knowledge associated with the invention ‘spills over’ within firms or industries and also between firms or industries. Such ‘knowledge effects’ are very important for industries operating on advanced technologies like green technologies, since they do not only shape and direct technological progress but also affect market competition and the incentives for innovation activities (Shapiro 2011). Consequently, they are of considerable meaning for explaining and understanding economic processes. They influence innovation activities on several levels (Cohen et al. 2002, Peri 2005), contribute to the diffusion of new technologies (Jaffe 1989, Keller 2002), provide opportunities for entrepreneurial activities (Audretsch 1995, Audretsch and Lehmann 2005), increase productivity (Griliches 1992, Moretti 2004), and ultimately generate economic growth (Grossman and Helpman 1991).

At the level of innovation activities spillovers from knowledge accumulation are essentially contributing to the innovativeness. At the firm level Blundell et al. (1995) or Crepon et al. (1998) identified a strong positive relationship between knowledge capital on the one hand, and patent activities or innovativeness on the other hand. Also at the industry level, Dosi (1984) showed for the semiconductor industry that innovation advantages are resulting from an accumulated knowledge stock. US companies early invested in semiconductors and gained a head start to the European and Japanese competitors and they stayed ahead of competitors even once the technology matured and its commercial perspectives became clearer. Knowledge does not only ‘spill over’ within firms or industries but also between firms or industries (Jaffe 1986, Jaffe et al. 1993). Hence, we expect that the size of internally and externally available green knowledge is positively correlated with the focal industry's current innovation activities in green technologies.[7]

Spillover effects should not be limited to green technologies alone, but may also come from non-green technologies. Since many green technologies are in a rather early phase of development and they are just about to penetrate markets, knowledge and experiences in other fields of advanced technologies are likely to play an important role in their development. It is likely that advanced knowledge in e.g. chemistry or engines increases the propensity of green research activities. This is especially true if there are 'economies of scope' in research activities (see Henderson and Cockburn 1996 for the pharmaceutical industry), i.e. synergies between different R&D projects or lines of research. For instance, an industry with knowledge and experiences in turbine development and production has capability advantages to diversify into steam turbine for biomass energy, solar energy, or energy from abatement. Or the chemical industry has knowledge advantages in order to make the dyeing process of clothes more environmentally friendly (save water, energy, and abatement). Hence, such industries can refer to internal non-green knowledge and do not need to begin from scratch in order to develop green technologies. Consequently, we would expect to see positive spillover effects of non-green knowledge on green invention activities as well.

Path dependency effect

As we look at two types of technologies, i.e. green and non-green technologies, the just mentioned positive 'spillover effect' of available knowledge has a flip side. Available knowledge and experience in non-green technologies represents opportunity costs that may lead to 'path dependency' and affect the decision to invest in green technologies. The mechanisms behind path-

[7] While there is some literature that finds that knowledge spillovers are geographically very limited (see Audretsch and Feldman 1996, Bottazzi and Peri 2003, Maurseth and Verspagen 2002) there is also evidence for substantial knowledge effects across borders (see Bottazzi and Peri 2007).

dependency or technological lock-in (David 1985, Arthur 1989) is fourfold. Lock-in effects are related to increasing returns from technological use driven by, e.g., positive scale economies and learning economies (see Arthur 1994). Moreover increasing returns result from the concept of “adaptive expectations” which increases the confidence in the quality and usefulness of a technology for both, producers and users. Increasing returns are also a consequence of positive network externalities due to an increasing number of adopters (Maréchal 2007). However, increasing returns and consequently the lock-in effect might be lower in the initial periods of technological development (see Foray 1997).

Such ‘path dependency’ or technologically lock-in is a well-known phenomenon in the history of technical change. The QWERTY keyboard (see David 1985), the US Ice-Industry, or the typewriter industry (see Utterback 1996) are famous examples of industries that did not change timely their technological basis. The German chemical industry after World War II is a further example that painfully shows the adverse consequences of a technological lock-in (see Stockes 1994). Skills, education, and attitudes that have been developed under the traditional technological regime delay or even prevent a timely change to newer technologies. Also investments in new technologies can be hindered or delayed through ‘sunk’ investments in traditional technologies. Accordingly we expect that due to the large opportunity costs, firms or industries with a large stock of non-green patents will be more likely to invest in non-green technologies today (see Aghion et al. 2015) and they are less likely to invest in green technologies. Clearly, path dependency also exists in green technologies, i.e. industries with an already large green knowledge stock are more likely to further invest in green knowledge.

Besides internal obstacles, technological change can also be affected by the technological environment or network externalities (see Maréchal 2007). A firm or an industry in a business environment that intensively uses green technologies will find it more profitable to invest in green technologies.[8] Instead, a business environment that primarily uses non-green technologies will make it more attractive for a firm or an industry to invest also in non-green rather than green technologies. Based on these path dependency effects, we thus assume that a firm or an industry in a business environment (home country, foreign countries) with a large stock of green (non-green) patents will be more likely to invest in green (non-green) innovations today.

Net effect: combination of spillover and path dependency effect

In sum it is obvious that technical change is a quite complex issue and difficult to frame into clear hypotheses. Based on the argumentation above it is necessary to combine the spillover effects and the path dependency effects in order to formulate research hypotheses. Table 1 arranges the relationship between both effects and the different sources of knowledge stocks. Consequently, Table 1 stylizes the findings to frame our hypotheses. However, we have to be aware that theory is not sufficiently detailed to allow for hypotheses in all dimensions of Table 1, i.e. 'spillover effect' and 'path dependency effects' and geographical location (i.e., internal, home country and foreign countries). In order to formulate clear hypotheses we thus refer to empirical evidence for the impact of knowledge stocks on green innovation activity.

In line with our predictions (columns 1 and 3 of Table 1), Aghion et al. (2015) find for the auto industry that the stocks of internal and country green knowledge are positively related to the number of green patents. With respect to the effect of internal non-green knowledge, they furthermore find that the size of a firm's non-green knowledge stock has a positive effect on green innovation; the impact of country non-green knowledge stocks, however, is negative. Consequently, we would also assume for the investigation at hand that internal non-green

[8] There may also be a competition effect. As there is competition at the industry and country level, a large knowledge stock within a certain technology may force other industries or countries to innovate in other technological fields. Hence, a large green country or foreign stock may decrease a focal industry's incentives to conduct green invention activities. However, as we only differ between green and non-green knowledge and do not focus on more specific technologies, such competition effects should be moderate in our case.

knowledge accumulation is positively related to current green patent applications (column 2 of Table 1) and that country non-green knowledge stocks are negatively related (column 4 of Table 1).

Moreover, there are some studies that analyze the effect of different knowledge stocks at the country level, i.e. they can only distinguish between internal and external knowledge, but not between different types of external knowledge.[9] Verdolini and Galeotti (2011) analyze the impact of internal and external knowledge in energy technologies for a panel of 17 countries. Their results show that both have a significant positive impact on further innovation, which is in line with our predictions of columns 1, 3 and 5 (Table 1), respectively. Further evidence for the predicted positive effect of external green knowledge can be found in Popp (2006). Based on patent citation data he finds in the case of air pollution control patent activities that the relevant knowledge stock in foreign countries influences the technological activities in the United States and vice versa. This is especially true for early foreign patents; they serve as a building block for green innovations in other countries. Related evidence is presented in the work by Popp et al. (2011). They analyze the impact of available knowledge on the investment in green technologies, and they detect a positive influence of world patent applications of certain green technologies on domestic investment activities in green technologies. Even if the effect of such technology-induced technical progress appears to be moderate, this again is in line with the expected positive effect for external green knowledge in our framework.

Based on the discussion above and the assumption that the effects of the different knowledge stocks on a focal industry's gap to the technological leader point in the exact *opposite* direction than their effects on the focal industry's current level of green innovation activities, i.e. what does increase the "level" decreases the "gap" (see beginning of Section 2.2), we can now formulate our

[9] As our study is at the industry level, their definition of external knowledge reflects a combination of the effects of country and foreign knowledge in our framework.

hypotheses. We expect that an increase of the *green* knowledge stock of the focal industry, the home country and foreign countries, respectively, reduces a focal industry's gap to the technological leader. Furthermore, an increase in the (home) country's *non-green* knowledge stock should increase the focal industry's gap to the green technological leader, but an increase in the internal non-green stock should reduce the gap to the leader. As the relationship between non-green knowledge in foreign countries and current green innovation activities has not been analyzed before, it is not possible to formulate a clear hypothesis for the effect of foreign non-green knowledge on our dependent variable. However, given the assumption that the effect of foreign non-green knowledge stocks and country non-green knowledge stocks are similar, we can expect a positive effect of a foreign non-green knowledge stock on the focal industry's gap to the green technological leader. All predictions are summarized in Table 1.

As it has already been mentioned in the introduction, it is interesting to see from a political point of view, if an increase of an industry's non-green knowledge also reduces its gap to the green technological leader. If this is the case, an industry is likely to have sufficient absorptive capacity for green technology achievements. This does not mean that they can successfully enter the market any time. It just indicates that policy measures would still find a technological environment where they have a chance to be effective, since the technological distance of such firms to green technologies is not too great. In our framework, this would require a negative net effect of internal non-green knowledge.

Besides the direction of the knowledge effects, the relative size of the different effects is of political importance. Internal *non-green* knowledge only matters for catching-up, if its effect on the gap to the leader is not much smaller than the effect of internal *green* knowledge. Furthermore, to be able to make a statement about wait-and-see opportunities, it is important to know whether the effect of *internal* knowledge on the gap to the green leader is much larger than the effect of *external* knowledge. In case the effect of external knowledge is not significantly smaller, it is likely that technological latecomers can benefit from the research activities of other industries/countries to such an extent that a wait-and-see strategy is profitable, i.e. they avoid the high costs of exploring new green technologies and wait until dominant technological designs have evolved to enter the markets based on lower costs.

Unfortunately, the available literature does not allow us to formulate clear hypotheses referring to the relative size of the effects of different knowledge stocks on the gap to the green technological leader. We therefore formulate two open research questions:

R1: Does an industry's internal green knowledge have a larger decreasing effect than its non-green knowledge on the industry's gap to the green technological leader?

R2: Does an industry's internal (green or non-green) knowledge have a larger decreasing effect than the (green or non-green) knowledge in the home country or foreign countries on the industry's gap to the green technological leader?

3 Description of the data

We use patents in order to measure the green invention activities of an industry. Patent statistics have many disadvantages in measuring innovation output (see Griliches 1990). However, despite the fact that not all innovations are patentable and smaller firms are more reluctant to patent than larger firms, patent counts are still the best available source of data on innovation activities as it is readily available and comparable across countries (Johnstone et al. 2010).[10] This is especially true for green technological activities, since the OECD provides a definition of green technologies based on the patent classification.

The patent information in this paper has been gathered in cooperation with the Swiss Federal Institute of Intellectual Property (IPI). Green patents are a sub-group of patents that are selected

[10] Levin et al. (1985) also found that appropriability significantly varies across industries. Hence, spillovers might differ across industries as well. In our econometric framework we control for such effects by industry-country fixed effects.

according to the OECD Indicator of Environmental Technologies (see OECD 2012)[11]. Based on the International Patent Classification, the OECD definition distinguishes seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting.[12]

In order to identify our proxy for the green knowledge output of an industry, further specifications and clarifications have to be made:

(a) In order to assign patents to countries, the applicant's country of residence or the inventor's country of residence may be chosen. We assigned patents according to the applicant's address.[13] Since only those inventions were selected for which at least one PCT (Patent Cooperation Treaty)

[11] Clearly, not all patents filed in these classifications must be "green" or to express it differently, depending on the category, the fraction of green patents might be different. However, we can be rather sure that we do not find green patents outside of these classifications. Hence, the OECD indicator seems to be a good "proxy" for the "green" technology intensity of an industry, if we count the patents in these categories and compare it with the patents in other categories

[12] While all these areas somehow deal with green technologies, the different areas have different characteristics that may also affect the relevance of the different knowledge stocks. To deal with this fact we additionally estimate our main model separately for each of the seven areas (see Table 7 and discussion in Section 5.3).

[13] We may also have used the inventor's address instead. However, there may be a risk of distorting the analysis, especially for smaller countries, because the inventor may not live in the country where the invention occurs. Conversely, by using the applicant's address the analysis may be biased by patent applications from multinationals for which the country of residence of the applicant possibly differs from the country where the invention occurred. In order to investigate if there are considerable differences, we took both the inventor's information and the applicant's information for Germany. In fact, we did not see any significant differences between the analysis based on the inventor's and applicant's address for that country.

application was filed, the applicant's address was generally available. Patent applications are usually costly. Moreover, the fees for an international patent application under the PCT are generally higher than those for a national or regional patent application. It thus seems likely that companies only use the PCT application route if they expect the inventions in question to have a significant commercial potential at the international level.

(b) We collected inventions (patent families) rather than single patents. The patent data stem from the EPO (European Patent Offices) World Patent Statistical database (PATSTAT). Patents were grouped into patent families according to the PATSTAT procedure (INPADOC). This approach mitigates distortions caused by different national granting procedures and different application attitudes (USA for example has greater number of single applications for one invention compared to Europe).

(c) Our analyses are on the industry level. Consequently we use the Schmoch et al. (2003) concordance scheme to link patent information (technological fields) to industries.[14] Based on this concordance table we recoded our invention data into 22 manufacturing industry classes at the NACE two and three digit level, respectively.[15]

Our final data set includes invention data from 13 countries (Austria, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States). These 13 countries account for about 95% of all ‘green’ and ‘non-green’ inventions worldwide. Moreover, the data set includes 22 industries that capture the whole manufacturing sector and comprises the period 1980-2009.

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[14] Lybbert and Zolas (2014), suggest new methods for constructing concordances. In comparing different concordance, they confirmed that at a relatively coarse level (e.g., 2 digit), the Schmoch et al. (2003) concordance enable a useful empirical policy analysis.

[15] Both, the concordance scheme and the OECD Indicator of Environmental Technologies (see OECD 2012) are based on the patent classification. Hence, we can easily distinguish green from non-green patents at the industry level. This way we can identify for each industry class the total number of green and non-green patents.

Figure 1 shows the aggregated development of green inventions over time. In the beginning of our sample period, only a few green inventions were registered. The number of green inventions remained very low during the following five years. Between 1985 and 1995, the number slightly increased. A sharp increase in the number of green inventions can be observed after 1995. In 2009, 29,444 green inventions were protected worldwide. Due to low invention activity in general, the share of green inventions was quite instable at the beginning of our sample period and later stabilizes between 6-8%. A disproportional increase in green inventions can be observed after 2000. By 2009, the overall share of green inventions has increased to 11.6%.

More disaggregated descriptive statistics by country and industry are presented in Table 2. Most green inventions are patented in the industries ‘machinery’ (23%), ‘chemicals (excluding pharmaceuticals)’ (21%), ‘motor vehicles’ (16%) and ‘electrical machinery and apparatus’ (10%). The two industries ‘motor vehicles’ and ‘electrical machinery and apparatus’ are at the same time the most green intensive industries.

At the country level we see larger shares of non-green inventions being generated by larger countries. The USA, Japan, and Germany hold 40%, 17%, and 15%, respectively. Concerning the respective shares in total green inventions (see column 4 in Table 1), we see a different picture. Although the USA (31%), Japan (24%), and Germany (20%) also show the greatest green shares, the country ranking changes further down the line. The last column in Table 2 shows the ratio of green inventions to non-green inventions. Denmark (15%), Japan (13%) and Germany (13%) show the highest degree of specialization in green invention activities, followed by Austria (12%) and France (10%). In sum, we see from these descriptive statistics that green invention activities show a great heterogeneity across industries and across countries.

4 Empirical framework

There are several approaches to measure the “gap” between the technological leader and the technological followers. A stochastic frontier approach is the “state of the art” in order to estimate “inefficiencies” or the distance from the technological frontier in a well-defined production function framework, e.g. Cobb-Douglas (Green 2005b, Battese and Coelli 1992). However, such an approach is not suitable for the study at hand, as we cannot assume that green invention activities are significantly positive related with the productivity of firms; several studies show that the productivity effect of green inventions is likely to be insignificant or even significantly negative (Marin 2014, Soltmann et al. 2014). Hence, firms with considerable green inventions might have a relatively lower productivity level compared to firms with no or fewer green inventions. In this case a "classical" frontier estimation which is based on the strict framework of a production function hardly makes sense, since a greater distance to the frontier might refer to larger green invention activities.

Furthermore, applying a stochastic frontier approach to innovation success is hardly convincing, as it is difficult to reach consensus on a strict theoretical framework, which would be important to separate heterogeneity from efficiency in the estimated model (Green 2005a and Wang and Schmidt 2002 for the "left-out variable problem") and to ensure that the estimation of the technological inefficiency is unbiased; this implies that the estimations explaining the technological distance would be biased, too.

An alternative approach to stochastic frontier models in order to investigate the technological gap is provided by Verspagen (1991). He defines the technological gap as the difference between the knowledge stock of the leading entity and the knowledge stock of the following entity, whereas the "catching-up" notion refers to factors that decrease the differences between the two knowledge stocks. Although his investigation is at the country level, he provides a suitable estimation framework for the paper at hand. We apply his measure to green inventions at the industry level, whereas we define the technological gap for an industry i in country j at time t as

$$Green\_gap_{ijt} = ln\left(\frac{Green\_inventions_F}{Green\_inventions_j}\right)_{it}, \qquad (1)$$

where F is the country with the highest number of green inventions in industry i at a specific point in time t (see Griffith et al. 2004 for a similar definition based on total factor productivity).[16] The larger is $Green\_gap_{ijt}$ in absolute magnitude, the greater is the technological gap between the technological leader and a follower.

In a further step we identify factors that are important in order to explain *Green_gap*. Here we refer to the general framework of a knowledge production function (e.g. Jaffe 1986). We operationalize labor (L) as the industries' total number of employees. In order to identify the effect of the different knowledge stocks, we include the knowledge stock variables in addition to these standard input factor in our model (Aghion et al. 2015). Formally, we estimate the following knowledge production function:

$$\begin{aligned}
\ln(Green_gap_{ijt}) &= \ln(A) + \alpha \ln(L_{ijt-1}) + \varphi_1 \ln(Internal_green_stock_{ijt-1}) \\
&+ \varphi_2 \ln(Country_green_stock_{ijt-1}) + \varphi_3 \ln(Foreign_green_stock_{ijt-1}) \\
&+ \lambda_1 \ln(Internal_non_green_stock_{ijt-1}) + \lambda_2 \ln(Country_non_green_stock_{ijt-1}) \\
&+ \lambda_3 \ln(Foreign_non_green_stock_{ijt-1}) + \mu_t + \eta_{ij} + \varepsilon_{ijt},
\end{aligned} \tag{2}$$

where A is a constant and the parameter α represents the elasticity of labor. *Internal_green_stock* measures the stock of green inventions of an industry i, in country j at time t. *Country_green_stock* is the stock in green inventions accumulated in industries other than i in the home country j.

[16] In our framework, most technological leaders come from the USA. In fact, 481 of the technological leaders in our final estimation sample come from the USA, which represents a share of 46%. The other technological leaders are quite evenly distributed across the other countries (Japan has a share of 11%; however, with shares of 6% and 5%, respectively, small countries like Denmark or Austria also have quite a lot green technological leaders). The dominance of the USA as technological leader should not affect our estimation results for two reasons. First, our models include country fixed effects. These fixed effects control for an industry's country-specific disadvantage in the number of patents. Hence, a potential (time persistent) negative bias of, e.g., Danish industries in our gap measure is captured by the country dummies. Second, our models control for the industries' number of employees, which captures the effect of potential size shocks over time. In sum, the effect of the different knowledge stocks on our gap measure should thus neither be affected by country-specific nor industry-specific size.

Foreign_green_stock is the stock of accumulated green knowledge in the same industry i in other countries than j. To capture potential effects of available knowledge in non-green technologies, we also control for the stocks of inventions that are not classified as green (*Non_green_stock*). φ and λ are the coefficients of the knowledge stocks and ε is the stochastic error term (see Table 3 and Table A.1 in the appendix for variable description and correlation matrix, respectively).

Following Cockburn and Griliches (1988) and Aghion et al. (2015), the stocks of inventions are calculated using the perpetual inventory method. Following this method, the stock of inventions is defined as

$$Green\_stock_{ijt} = (1-\delta)Green\_stock_{ijt-1} + Green\_inventions_{ijt}, \qquad (3)$$

where δ is the depreciation rate of R&D capital.[17] According to most of the literature, we take δ to be equal to 15% (see Keller 2002, Hall et al. 2005). However, we test the sensitivity of our results to other depreciation rates as well (see Table 6). The stock of non-green inventions is calculated in the same way as the stock of green inventions.

As patent variables can take on the value 0, we used the original variables plus 1 to avoid problems with the logarithm (see Wooldridge 2002, p. 185). To deal with the potential problem of reverse causality the independent variables are introduced with a lag of one year. To control for correlated unobserved heterogeneity, we include country-specific industry fixed effects (η). Furthermore, we also include year fixed effects (μ). Potential problems with unobserved heterogeneity are discussed in more detail in Section 5.2.

As the time series dimension of our data is quite long and the patent data series are likely to be persistent, the results for the "knowledge" variables may be driven by non-stationarity. In order to

[17] Due to the low number of patents before 1980, we restricted our sample period to the years 1980-2009. However, we use patent applications between 1975 and 1980 in order to calculate pre-sample invention stocks. The initial value of the invention stock is set at $Green\_stock_{1975}/(\delta+g)$, where g is the pre-1975 growth in invention stock that is assumed to be 15%.

deal with this issue, we perform unit root tests for all “knowledge” variables included in the regressions. We employ three different tests proposed by Levin et al. (2002), Im et al. (2003) and Pesaran (2007), respectively. Based on all three tests we can reject the unit root assumption for any of the “knowledge” variables (see Table A.2 in the appendix).

5 Estimation results

5.1 Main results

Table 4 presents the main results that are based on an OLS log linear fixed effects estimator. In line with our predictions, an increase of the focal industry’s ‘internal green stock’ and ‘country green stock’ decreases the industry’s gap to the green technological leader. This negative net effect on the gap indicates positive ‘spillover’ and ‘path dependency’ effects not only from the internal green knowledge stock but also from the green technology environment in the home country. Surprisingly, we cannot observe a similar effect for the ‘foreign green stock’, i.e. green knowledge in the focal entity’s industry in other countries even increases the focal industry’s gap to the green technological leader. An explanation for this unexpected result is that an industry’s global green knowledge does not only affect the green invention activities of the focal industry, but also the green invention activities of the industry’s green technological leader (see also discussion in footnote 6). In fact, we observe - in a different econometric setting - a significant positive effect of foreign green knowledge on the focal industry’s current flow of green inventions (see Table A.3 in the appendix), which is in line with our previous prediction (see Table 1). However, as the industry’s technological leader seems to benefit more compared to its followers, the positive effect on the focal industry’s current flow of green inventions does not result in the expected negative net effect on the focal industry’s gap to the technological leader.[18]

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[18] However, the negative effect of the foreign green stock is not a pure mechanical effect driven by the fact that the foreign green stock also depends on the knowledge of the technological leaders. In further estimations not presented

With respect to non-green knowledge, we observe the expected positive effects for ‘country non-green stock’ and ‘foreign non-green stock’, indicating that external non-green knowledge increases the focal industry’s gap to the green technological leader. Accordingly, ‘path dependency’ dominates the effect of *external* non-green knowledge. ‘Path dependency’ is also of high importance for *internal* non-green knowledge, since the observed effect for ‘internal non-green knowledge’ is positive and insignificant. This insignificant effect may be explained by relative little spillovers or few synergies between green and non-green knowledge, which do not overcompensate the countervailing path dependency effect. This explanation is supported by the fact that we do not only observe an insignificant effect of the focal industry’s internal non-green knowledge on the gap to the leader, but in a different econometric setting also an insignificant effect on the focal industry’s level of green inventions (see Table A.3 in the appendix), for which we actually had expected a significant positive effect.

In order to deal with the two research questions, we now have to compare the size of the different knowledge effects. In doing so, we apply Wald tests that pair-wise compare the size of the different coefficients. With respect to our first research question that contrasts the effect of green and non-green knowledge, we observe that ‘internal green knowledge’ (p-value for test of equality of coefficients: 0.00) and ‘country green knowledge’ (p=0.00) both are significantly more important to reduce the focal industry’s technological gap to the leader than their non-green counterparts, but we do not observe significant differences between the two positive effects of foreign green and non-green knowledge (p=0.58). In sum the results thus clearly show that green knowledge is crucial for remaining competitive in terms of green inventions. Due to large path dependency effects, non-green knowledge even tends to increase an industry’s gap to the green technological leader.

here, we received very similar results when we exclude the green knowledge of the leader from the foreign knowledge stock measure (results are available on request).

Concerning the respective effects of internal and external knowledge, we find that 'internal green knowledge' decreases the gap nearly twice as much as 'country green knowledge'. As 'foreign green knowledge' even tends to increase the gap between leader and followers, it is thus not surprising, that 'internal green knowledge' is significantly more important to reduce an industry's gap to the green technological leader than the two pools of external green knowledge (country knowledge: p=0.00; foreign knowledge: p=0.00). Although 'internal non-green knowledge' tends to widen the "gap" (positive but insignificant effect), the magnitude of its positive effect is significantly smaller than the gap increasing effects of 'country non-green knowledge' (p=0.01) and 'foreign non-green knowledge' (p=0.01), respectively.[19] These results indicate that the magnitude of internal knowledge is significantly more valuable than external knowledge in reducing an industry's gap to the green technological leader; hence, the spillovers tend to decrease with the geographical and technological distance and the path dependency effect (relatively) gains in importance.

A potential problem of the data may be, that the distribution of inventions across industries is very heterogeneous. In order to test the robustness of our results, we thus run our estimation excluding the top 1% of performers and the top 5% of the performers, respectively (see Table A.4 in the appendix).[20] This does not affect the direction and the relative size of the knowledge stock coefficients. We thus conclude that our results are not driven by outliers.

[19] Within external knowledge sources we find that the negative effect of 'country green knowledge' significantly differs from the positive effect of 'foreign green knowledge' (p=0.00). The positive effects of country and foreign non-green knowledge do not significantly differ from each other (p=0.78).

[20] Our main estimates presented in Table 4 are based on 262 groups. To check for outliers, we excluded all groups with an average clean or dirty invention stock greater THAN or equal to the top 1% and 5% of the groups, respectively. All in all, we thus dropped 4 and 18 groups that account for 1.7% and 7.0% of the observations, respectively.

5.2 Unobserved heterogeneity

Following Porter and van der Linde (1995) there is some evidence that environmental policies stimulate green invention activities. As the gap to the technological leader, our dependent variable, and the knowledge stock variables, our main independent variables, are composed of passed and/or current green invention activities, it is thus possible that environmental policy simultaneously affects our dependent variable and the stock variables. By including country-specific industry fixed effects, our baseline model at least controls for the industry-country-specific fixed political environment, i.e. the industry-specific policy affinity of a country. Besides such long-term policy effects, the results may, however, also be affected by policy shocks, i.e. changes in the policy framework. Global policy shocks are captured in our model by the inclusion of time fixed effects. Nevertheless, the results would be biased if there are political shocks at the country and/or industry level affecting our dependent variable and the stock variables. However, as the stock variables represent the accumulated patenting activities over several years, it is quite unlikely that a *shock* significantly affects both the stock variables and our dependent variables.[21] Nevertheless, we apply several tests in order to identify a potential omitted variable bias.

In order to test the impact of country-specific policy shocks, we separately add two different country-specific policy measures to our baseline model (see Table 5). In column 1 we include the total tax on light fuel oil, in column 3 we add public sector total energy RD&D spending. In contrast to alternative measures, these two measures are available for all countries that are included in our sample and for a relatively long time period. Nevertheless we lose some observations. In order to test whether the inclusion of these policy variables leads to a selection problem due to missing observations, columns 2 and 4 show the respective estimates for the same set of observations but excluding the policy measures. In line with general predictions, both policy variables show a

[21] If the political environment affects the invention activities over a longer time period, this should be captured by the country-specific industry fixed effects.

negative effect on the distance to the technological leader (although the effect of RD&D spending is just not statistically significant), i.e. both policy variables indicate a reduction of the gap to the technological leader. The inclusion of the policy variables does, however, not influence the effect of the stock variables. Hence, we conclude that our results are unlikely to be affected by unobserved policy shocks at the country level.

However, there could still be industry-specific unobserved heterogeneity in our model. As it is hardly possible to find adequate policy measures at the industry-country level for such a long time period, it is not possible to directly control for industry-specific policy shocks. In order to get an idea whether our results might be affected by such a bias, we vary the depreciation rate that is used to calculate the stock variables. The idea behind this exercise is that by *increasing* the depreciation rate, we increase the weight of the patenting activities of the last year and devaluate the accumulated knowledge of previous years. This makes it more likely that a policy shock simultaneously affects the patents of the current year (dependent variable) and the knowledge stocks, which then mainly consists of the patents in the last year. By *decreasing* the depreciation rate, we decrease the weight of the patenting activities of the last year, emphasizing the importance of the accumulated knowledge of previous years, which is less likely to be effected by a policy shock. This in turn decreases the likelihood that a policy shock biases our results.[22] The estimation results for alternative depreciation rates of 10% and 30%, respectively, are presented in Table 6. The results show that neither the direction nor the relative size of the knowledge effects is affected

[22] In the case the depreciation rate amounts to 100% we would just observe the patent flow in t-1 and hence it is likely that a policy shock effects both, the “stock”, which is the flow in t-1, and the current flow of green inventions. If we had a depreciation rate of 0% than we would have the sum of all past inventions represented by our “stock” variable and consequently a policy shock in a certain period would have a minor effect on the “stock”. Now, if we see that the depreciation rate does not significantly impact the results, it is likely that our results are not biased due to omitted policy controls.

by varying the depreciation rate. Hence, we conclude that it is rather unlikely that our results are biased by omitted policy controls at the industry-country level.

5.3 Estimates for different areas of green inventions

Our estimates so far have been based on a quite broad definition of green inventions which actually consists of seven environmental areas. The seven environmental areas are quite heterogeneous and may thus have different characteristics in terms of market relevance, technological potential, or their technological proximity to non-green technologies. Consequently, spillovers and path dependency are of different magnitude and the relevance of the different knowledge pools may differ between these areas. To investigate this assertion, we estimate our baseline model separately for the seven environmental areas considered by the OECD Patents statistics (OECD 2013).

We separate two types of green knowledge for each environmental area in order to capture differences in the effects between *technology-specific* green knowledge and knowledge in other green technologies ('nonspecific green stocks'). For instance, if we look at the environmental area 'general environmental management', we separate the green stock referring to 'general environmental management' from the green stocks referring to all other environmental areas (e.g., 'energy generation form renewable and non-fossil sources', 'energy efficiency in buildings and lighting'). We did this for internal-, country-, and foreign green stocks, respectively. As in all previous models, non-green knowledge still refers to knowledge in technologies that are not classified as green. The respective estimation results are presented in Table 7.

The results for (area-)*specific green knowledge* are very similar to our previous findings for green knowledge at the aggregated level. Firstly, 'specific internal green knowledge' and 'specific country green knowledge', respectively, show significantly negative effects for all areas, i.e. they decrease the gap to the leader. Secondly, the effects of 'specific foreign green knowledge' turns out to be significantly positive for all areas. Furthermore, the relative size of the coefficients is in line with our previous findings for green knowledge at the aggregated level. At the area level, the negative coefficients of 'specific internal green knowledge' are between two and six times as large as the corresponding coefficients of ‘specific country green knowledge’. Hence, the relative importance of internal green knowledge is even slightly larger at the area level than at the aggregated level.

With respect to *non-area-specific green knowledge* it is not a priori clear whether it behaves more like green knowledge or like non-green knowledge. The results show that the effects of non-area-specific green knowledge are more similar to the effects that we observed at the aggregated level for green knowledge than for non-green knowledge. Firstly, the effects of internal non-area-specific green and country non-area-specific green knowledge are mostly negative. Secondly, foreign non-area-specific green knowledge increases the gap to the technological leader in most areas.

The pattern for *non-green knowledge* significantly differs from the findings at the aggregated level. Firstly, while the elasticity of ‘internal non-green knowledge’ was nearly zero at the aggregated level, it now shows significantly positive effects for most areas of green technologies. These results indicate that the effect of internal path dependency increases when we focus on the single areas of the OECD definition for environmentally friendly technologies. The fact that ‘internal non-specific green knowledge’ shows significantly positive effects for two areas as well, further supports the view that path dependency accentuates at the area level.

Secondly, while the effect of ‘foreign non-green knowledge’ was significantly positive at the 1% test level in the main model mirroring path dependency effects, such a (significant) positive, gap-increasing influence could not be found in all seven areas; in some areas it even tends to decrease the gap. This indicates that spillovers from non-green knowledge in the focal entity’s industry in other countries get more important when we focus on single areas of green inventions. In addition to such spillovers, spillovers from *non-specific* green knowledge seem to be very relevant at the area level as well, i.e. the gap diminishing net-effect of ‘country non-specific green knowledge’ tend to be relatively large, while the gap increasing net-effect of ‘foreign non-specific green knowledge’ is relatively small.

Even though there are some interesting differences when analyzing the knowledge effects at a more disaggregated level of green technologies, the main findings of these models are the same than for our main models. In sum, the disaggregated models indicate as well that *internal green knowledge* is crucial in order to reduce the gap to the green technological leader; while the positive spillover effect of external *non-green* knowledge seems to increase when analyzed at the disaggregated level, also the positive path dependency effect of internal *green* knowledge seems to increase, whereby the relative size of the internal and external knowledge effects remains more or less unaffected.

6 Discussion and conclusions

Based on industry level panel data the paper at hand investigates the meaning of different types of green and non-green knowledge stocks on the technological gap between the technologically leading industry and its followers. The econometric models and a number of robustness tests indicate that the magnitude of internal green knowledge is the key factor in order to be competitive in terms of green inventions.

More concretely we find that, firstly, internal green knowledge is more important than external green knowledge in order to decrease the gap to the technological leader. Although available green knowledge from other industries within a country contributes to diminish the gap to the leader, it can only marginally compensate the lack of internal green knowledge. Hence, the spillovers from internal sources of green knowledge seem to be much larger than the spillovers from external sources.

Secondly, internal green knowledge is more important than (internal and external) non-green knowledge in order to decrease the gap to the technological leader. This result contradicts the widely shared view that a strong knowledge base in *non-green* technologies reduces the risk of permanently lagging behind, since it is assumed that the technological distance between green and non-green inventions is low, and consequently firms can switch into green invention activities once markets are developed. Instead, our results show that internal non-green knowledge does not reduce the technological gap and external non-green knowledge even increases the gap to the green technological leader. Looking at the disaggregated level of green technological areas we even observe gap increasing effects of internal non-green knowledge for some areas.

As the technological proximity may depend on the characteristics of the green technology, the knowledge effects may vary across the different areas of green technologies. For instance, for ‘general environmental management’ the proximity to non-green technologies might be smaller compared to ‘energy generation from renewable and non-fossil sources’. Accordingly, the flexibility to switch from developing non-green to developing green technologies would be smaller in the latter case. However, as we do not observe gap decreasing effects of non-green knowledge for any of the areas of the OECD definition for environmentally friendly technologies, the finding of our main model that non-green knowledge cannot significantly help reducing the green gap is confirmed at the more disaggregated level as well.

Given that the identified relationships between the different knowledge stocks and current green inventions for the last 30 years do not fundamentally change in the near future, our results thus have clear policy implications. We can convincingly show that ‘path dependency’ matters in the development of green inventions and that it can be very costly in terms of future inventions to lose the connection to the technological frontier by missing the ‘momentum’ to invest in the development of internal green knowledge. Moreover, ‘spillovers’ from external sources of green knowledge seem to be moderate. Hence, a wait-and-see strategy does not seem to be a promising way to proceed if one wants to be at (or close to) the technological frontier and thus keeping alive the options to benefit economically from future markets for green technologies. Timely investments in the development of green inventions seem to be necessary. This is a lesson that we can also draw from the history of technological change. There are many examples, e.g. the semiconductor industry, that show how difficult it is to enter successfully technological markets as a latecomer (see, e.g., Dosi 1984). Hence, governments should not lose more time in seizing policy measures if they not only want to bear the costs of climate change, but also want to benefit from the expected economic gains related to the early generation of green technologies which have the potential of setting standards.

Extensions of our main model that additionally include policy variables indicate that policy instruments can directly reduce the gap to the leader. Hence, it is likely that industries are still receptive to green policies, which means that they are capable to react upon relatively weak policy signals and - consequently - that the technological gap between green and non-green technologies seems to be not too big for the time being. The literature suggests a portfolio of policy measures, including carbon prices, R&D subsidies, and regulation (Aghion et al. 2009) to effectively promote green innovation activities and consequently increase the green knowledge stock and potentially decrease the gap. Similarily, Veugelers (2012)[23] confirms the portfolio perspective and emphases the importance of intertemporal consistency of policy especially for climate change innovations. Johnston et al. (2010) found that the policy effectiveness varies over technologies. Quantity-based policy instruments, such as obligations or tradable certificates are effective for the generation of wind power technologies, whereas direct investment policies, such as taxes, tend to be more effective for the generation of solar and waste-to-energy technologies. Lanoie et al. (2011) add to the policy effectiveness discussion that overall policy stringency induces green technology development and consequently the accumulation of green knowledge.

The fact, that the coefficients of green and non-green knowledge stocks are significantly different, signalizes that it is necessary to promote the accumulation of internal green knowledge. Policy instruments that push investments in non-green technologies may even have a countervailing effect, as non-green knowledge typically increases the gap to the green technological leader.

In line with Porter and van der Linde (1995) and Acemoglu et al. (2012) we thus conclude that if a country does not timely provide attractive framework conditions for the development of green technologies, there is a risk of remaining uncompetitive for a long time. Hesitation in policy action

[23] Veugelers (2012) also provides an excellent overview of policy effectiveness.

can be very costly, especially for developed countries with high labor costs, since to copy green technologies developed elsewhere and entering the markets based on price competition seems to be not a viable strategy for them.

Further research is necessary to identify adequate policy measures and strategies in policy setting, to profound our knowledge for policy effects, and to quantify the performance effects of policy-induced, green inventions. Moreover, further research should elaborate on the technological proximity between green and non-green technologies in greater detail and consequently identify if the overall results still hold. Future research could also compare the ‘knowledge stock’ patterns of green technologies with other types of technologies, e.g. fuel cells, biotechnology, nanotechnology.

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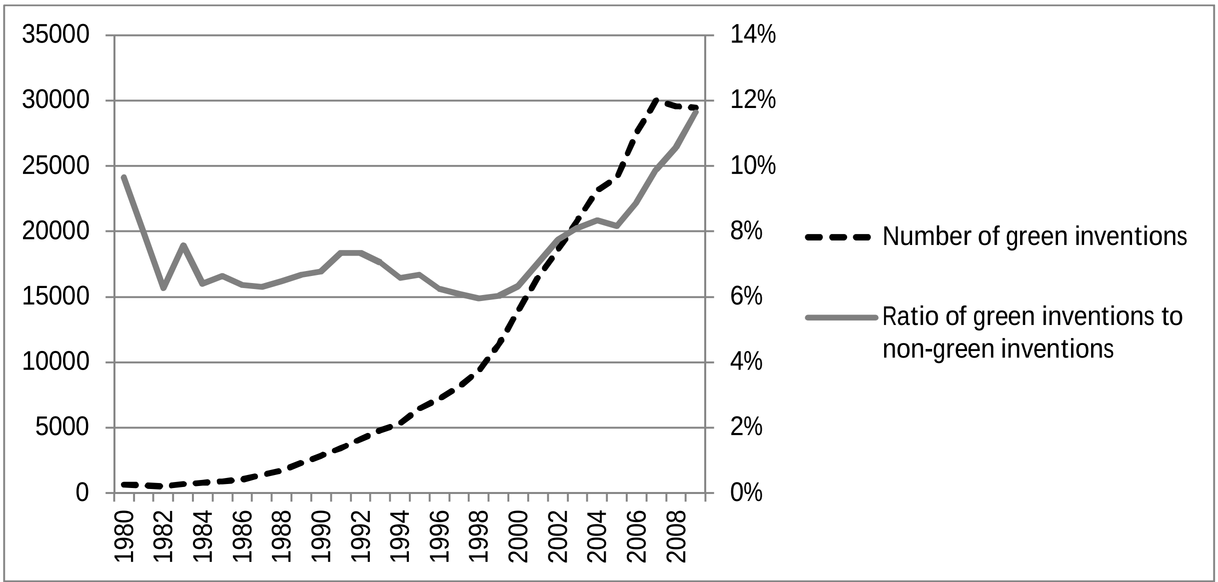
Table 1: Expected direction of the knowledge effects by different sources

		Internal knowledge		Country knowledge		Foreign knowledge	
		Green	Non-green	Green	Non-green	Green	Non-green
Effect on current green invention activities:	*Theoretical predictions:*						
	- Spillover effect:	+	+	+	+	+	+
	- Path dependency effect:	+	-	+	-	+	-
	Net effect:	+	**?**	+	**?**	+	**?**
	Empirical findings:						
	Aghion et al. (2015)	+	+	+	-	n/a	n/a
	Verdolini and Galeotti (2011)	+	n/a	+	n/a	+	n/a
	Popp (2006)	n/a	n/a	+	n/a	+	n/a
	Popp et al. (2011)	n/a	n/a	+	n/a	+	n/a
Expected effect on gap to the green technological leader:		-	-	-	+	-	+

Notes: Popp (2006), Popp et al. (2011) and Verdolini and Galeotti (2011) are based on country-level data. Hence, their findings for the effect of knowledge from foreign countries on innovation in the home country can be interpreted as external knowledge effect, but their investigation does not allow for a distinction between country and foreign knowledge effects.

Figure 1: Development of green inventions worldwide, 1980-2009



Source: Own calculations.

Table 2: Number of green and non-green inventions by industry and country

Period	1980-2009				
Type of invention	Non-green		Green		Green vs. non-green
	Number of non-green inventions	Relative share in total non-green inventions	Number of green inventions	Relative share in total green inventions	Ratio of green inventions to non-green inventions
Industry					
Food, beverages	49,344	1.74%	1,927	0.70%	3.91%
Tobacco products	2,455	0.09%	,68	0.02%	2.77%
Textiles	15,947	0.56%	,833	0.30%	5.22%
Wearing apparel	5,748	0.20%	,59	0.02%	1.03%
Leather articles	4,023	0.14%	,16	0.01%	0.40%
Wood products	4,251	0.15%	,170	0.06%	4.00%
Paper	21,948	0.77%	1,310	0.48%	5.97%
Petroleum products, nuclear fuel	16,727	0.59%	3,357	1.22%	20.07%
Rubber and plastics products	105,416	3.71%	5,259	1.92%	4.99%
Non-metallic mineral products	82,054	2.89%	9,047	3.30%	11.03%
Basic metals	46,234	1.63%	6,206	2.26%	13.42%
Fabricated metal products	63,096	2.22%	7,763	2.83%	12.30%
Machinery	448,752	15.80%	62,691	22.87%	13.97%
Office machinery and computers	295,643	10.41%	4,216	1.54%	1.43%
Electrical machinery and apparatus	95,880	3.38%	26,583	9.70%	27.73%
Radio, television and communication equipment	475,299	16.74%	23,116	8.43%	4.86%
Medical, precision and optical instruments	515,521	18.16%	12,278	4.48%	2.38%
Motor vehicles	104,022	3.66%	45,204	16.49%	43.46%
Other transport equipment	28,804	1.01%	2,431	0.89%	8.44%
Furniture, consumer goods	48,759	1.72%	,394	0.14%	0.81%
Chemicals (excluding pharmaceuticals)	323,411	11.39%	56,939	20.77%	17.61%
Pharmaceuticals	85,974	3.03%	4,220	1.54%	4.91%
Country					
Austria	27,921	0.98%	3,422	1.25%	12.26%
Switzerland	84,590	2.98%	5,804	2.12%	6.86%
Germany	421,402	14.84%	54,676	19.95%	12.97%
Denmark	26,491	0.93%	3,917	1.43%	14.79%
Finland	47,816	1.68%	3,356	1.22%	7.02%
France	162,619	5.73%	16,752	6.11%	10.30%
United Kingdom	170,265	6.00%	14,743	5.38%	8.66%
Ireland	9,343	0.33%	,623	0.23%	6.67%
Italy	52,229	1.84%	4,572	1.67%	8.75%
Japan	490,432	17.27%	64,858	23.66%	13.22%
Netherlands	114,890	4.05%	8,573	3.13%	7.46%
Sweden	93,483	3.29%	6,729	2.46%	7.20%
United States	1137,827	40.07%	86,062	31.40%	7.56%
Total	**2839,308**	**100.00%**	**274,087**	**100.00%**	**9.65%**

Notes: Data is based on own calculations; these statistics are based on 30 cross-sections, 13 countries and 22 industries (total of 8,580 observations); the relative share in total green inventions is calculated as the share of an industry's/country's number of green inventions relative to the number of all green inventions in our sample (sum of green inventions over all industries/countries in the sample); the ratio of green inventions to non-green inventions is defined as an industry's/ country's ratio of green inventions relative to its number of non-green inventions.

Table 3: Variable definition and measurement

Variable	Definition/measurement	Source	Mean	Std. Dev.	Min	Max
Dependent variable						
Green_gap$_{ijt}$	Gap to the green technological leader	own calculations	129.43	280.84	0	1744
Green_inventions$_{ijt}$	Number of green inventions	own calculations	37.45	145.42	0	1764
Independent variable						
L$_{ijt}$	Number of persons engaged (total employment)	OECD STAN database (OECD 2011b)	188768.70	318722	100	1933034
Internal_green_stock$_{ijt}$	Stock of green patents in industry *i* in country *j*	own calculations	132.49	557.07	0	8432.81
Country_green_stock$_{ijt}$	Stock of green patents in industries other than *i* in the home country *j*	own calculations	2706.94	5858.70	0	35963.46
Foreign_green_stock$_{ijt}$	Stock of green patents accumulated in industry *i* in countries other than *j*	own calculations	1665.12	3902.19	0	30899.01
Internal_non_green_stock$_{ijt}$	Stock of patents that are not classified as green in industry *i* in country *j*	own calculations	1476.17	5768.03	0	97872.28
Country_non_green_stock$_{ijt}$	Stock of patents that are not classified as green in industries other than *i* in the home country *j*	own calculations	30517.84	66875.67	3.7	451596.20
Foreign_non_green_stock$_{ijt}$	Stock of patents that are not classified as green accumulated in industry *i* in countries other than *j*	own calculations	18533.72	36932.81	9.5	230837.60
Lightfueloil_taxes$_{jt}$	Total tax (USD/unit using PPP) on light fuel oil for households	IEA (IEA 2015a)	170.76	169.56	0	771.84
Public_energy_RD&D$_{jt}$	Public sector total energy RD&D spending (Million USD using PPP)	IEA (IEA 2015b)	1014.37	1494.19	1.83	9399.53

Notes: The descriptive statistics for most variables is based on the estimation sample of Table 3 (6818 observations); exceptions are the statistics for the variables Lightfueloil_taxes$_{jt}$ that is based on the estimation sample of column (1) of Table 5 (6334 observations) and Public_energy_RD&D$_{jt}$ that is based on the estimation sample of column (3) of Table 5 (5995 observations); i, industry; j, country; t, time.

Table 4: Estimation results of main model

	OLS log linear fixed effects regression
	$\ln(Green\_gap_{ijt})$
$\ln(L_{ijt-1})$	.26107***
	(.06429)
$\ln(Internal\_green\_stock_{ijt-1})$	-.445***
	(.02833)
$\ln(Country\_green\_stock_{ijt-1})$	-.23941***
	(.0635)
$\ln(Foreign\_green\_stock_{ijt-1})$	.37825***
	(.04637)
$\ln(Internal\_non\_green\_stock_{ijt-1})$	.0062
	(.04442)
$\ln(Country\_non\_green\_stock_{ijt-1})$	.27917***
	(.08323)
$\ln(Foreign\_non\_green\_stock_{ijt-1})$	.31429***
	(.09547)
$Constant_{ijt}$	-5.1003***
	(.9077)
Year fixed effects	yes
Country-specific industry fixed effects	yes
N	6818
Groups	262
F	40.99***
R^2 within	0.40
Rho	0.72

Notes: see Table 3 for the variable definitions; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; i, industry; j, country; t, time.

Table 5: Add policy controls

	(1)	(2)	(3)	(4)
	OLS log linear fixed effects regression			
	$\ln(\text{Green\_gap}_{ijt})$			
$\ln(L_{ijt-1})$	.25969***	.26067***	.15616**	.15206**
	(.06628)	(.0646)	(.06544)	(.06488)
$\ln(\text{Internal\_green\_stock}_{ijt-1})$	-.40673***	-.41736***	-.42867***	-.42795***
	(.0292)	(.03037)	(.03024)	(.03013)
$\ln(\text{Country\_green\_stock}_{ijt-1})$	-.22011***	-.28933***	-.3729***	-.38491***
	(.05559)	(.06336)	(.09264)	(.09444)
$\ln(\text{Foreign\_green\_stock}_{ijt-1})$	.37782***	.38428***	.33956***	.33957***
	(.04649)	(.04614)	(.04896)	(.04885)
$\ln(\text{Internal\_non\_green\_stock}_{ijt-1})$	-.01107	.00354	-.03983	-.03559
	(.04472)	(.0446)	(.05239)	(.05252)
$\ln(\text{Country\_non\_green\_stock}_{ijt-1})$	.23153***	.31027***	.44553***	.46842***
	(.07654)	(.0825)	(.12809)	(.13274)
$\ln(\text{Foreign\_non\_green\_stock}_{ijt-1})$	.36879***	.35498***	.35504***	.35152***
	(.09578)	(.09732)	(.10607)	(.10613)
$\ln(\text{Lightfueloil\_taxes}_{jt-1})$	-.1102***			
	(.03403)			
$\ln(\text{Public\_energy\_RD\&D}_{jt-1})$			-.04701	
			(.03229)	
Constant_{ijt}	-4.8488***	-5.3756***	-4.1775***	-4.5034***
	(.88032)	(.86723)	(1.0138)	(1.0393)
Year fixed effects	yes	yes	yes	yes
Country-specific industry fixed effects	yes	yes	yes	yes
N	6334	6334	5995	5995
Groups	262	262	262	262
F	52.44***	54.20***	25.11***	25.65***
R^2 within	0.42	0.42	0.33	0.33
Rho	0.76	0.74	0.62	0.66

Notes: see Table 3 for the variable definitions; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; i, industry; j, country; t, time.

Table 6: Estimates based on alternative depreciation rates

	(1)	(2)
	OLS log linear fixed effects regression	
	$\ln(Green\_gap_{ijt})$	
Depreciation rate	10%	30%
$\ln(L_{ijt-1})$	.26657***	.23911***
	(.06616)	(.05986)
$\ln(Internal\_green\_stock_{ijt-1})$	-.43161***	-.46744***
	(.02933)	(.02598)
$\ln(Country\_green\_stock_{ijt-1})$	-.25293***	-.21084***
	(.07038)	(.04926)
$\ln(Foreign\_green\_stock_{ijt-1})$	.37433***	.38218***
	(.05141)	(.03669)
$\ln(Internal\_non\_green\_stock_{ijt-1})$	.01977	-.02468
	(.04725)	(.03749)
$\ln(Country\_non\_green\_stock_{ijt-1})$	.29247***	.24075***
	(.09293)	(.06294)
$\ln(Foreign\_non\_green\_stock_{ijt-1})$	.30705***	.32316***
	(.10339)	(.07856)
$Constant_{ijt}$	-5.2084***	-4.6317***
	(.95401)	(.80753)
Year fixed effects	yes	yes
Country specific industry fixed effects	yes	yes
N	6818	6818
Groups	262	262
F	37.68***	50.97***
R^2 within	0.39	0.42
Rho	0.73	0.68

Notes: see Table 3 for the variable definitions; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; i, industry; j, country; t, time.

Table 7: Estimates for different areas of green inventions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Area of green inventions	General environmental management	Energy generation from renewable and non-fossil sources	Combustion technologies with mitigation potential	Technologies specific to climate change mitigation	Technologies with potential or indirect contribution to emission mitigation	Emission abatement and fuel efficiency in transportation	Energy efficiency in buildings and lighting
	OLS log linear fixed effects regression ln(Green_gap$_{ijt}$)						
ln(L_{ijt-1})	.25922***	.31267***	.03122	.05158*	.21494***	.14081**	.16394**
	(.0526)	(.06143)	(.03894)	(.03043)	(.04951)	(.0556)	(.06454)
ln(Internal_specific_green_stock$_{ijt-1}$)	-.26896***	-.287***	-.1873***	-.2329***	-.40654***	-.38751***	-.35936***
	(.03022)	(.03168)	(.03616)	(.03388)	(.03207)	(.02807)	(.0283)
ln(Country_specific_green_stock$_{ijt-1}$)	-.11155**	-.06325**	-.04779***	-.07954***	-.17345***	-.06463**	-.1547***
	(.05118)	(.03027)	(.01475)	(.01595)	(.02602)	(.02911)	(.02266)
ln(Foreign_specific_green_stock$_{ijt-1}$)	.3578***	.33186***	.34553***	.34747***	.44622***	.46803***	.44017***
	(.03939)	(.03192)	(.02323)	(.01956)	(.03093)	(.02502)	(.02197)
ln(Internal_nonspecific_green_stock$_{ijt-1}$)	-.16653***	-.04597*	.02341	.07157***	.08104***	-.02944	.0134
	(.02647)	(.02482)	(.01986)	(.01795)	(.02969)	(.02808)	(.02377)
ln(Country_nonspecific_green_stock$_{ijt-1}$)	-.09498*	-.22963***	-.09047**	-.04255	-.08843	-.18602***	-.10494**
	(.04867)	(.04051)	(.04065)	(.03793)	(.05839)	(.05314)	(.05018)
ln(Foreign_nonspecific_green_stock$_{ijt-1}$)	.09471***	.08611**	.08374***	.00608	.1115***	.16703***	.05771*
	(.03397)	(.03729)	(.02796)	(.01802)	(.03434)	(.04165)	(.03107)
ln(Internal_non_green_stock$_{ijt-1}$)	.0266	.06929**	-.00118	.01242	.07111**	.06759*	.13702***
	(.03607)	(.03398)	(.02616)	(.02125)	(.03553)	(.03537)	(.03211)
ln(Country_non_green_stock$_{ijt-1}$)	.1602**	.29194***	.08953	.02712	.13807*	.20045***	.103
	(.06813)	(.05879)	(.06013)	(.05742)	(.07729)	(.07502)	(.07041)
ln(Foreign_non_green_stock$_{ijt-1}$)	.27417***	-.08284	-.12114*	-.03078	-.24059***	-.09374	.15926*
	(.08988)	(.08719)	(.06682)	(.05121)	(.09268)	(.07734)	(.09621)
Constant$_{ijt}$	-4.6897***	-4.1552***	-.10456	-.48582	-1.928**	-2.173***	-3.1207***
	(.80834)	(.83255)	(.59272)	(.47904)	(.84918)	(.73573)	(.93591)
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Country-specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes
N	6818	6818	6818	6818	6818	6818	6818
Groups	262	262	262	262	262	262	262
F	45.26***	46.15***	72.95***	122.27***	71.61***	58.38***	89.74***
R^2 within	0.41	0.45	0.38	0.53	0.53	0.49	0.57
Rho	0.66	0.70	0.25	0.28	0.60	0.54	0.67

Notes: see Table 3 for the variable definitions; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; i, industry; j, country; t, time.

APPENDIX

Table A.1: Correlation matrix (based on model of Table 4; 6818 observations)

	ln(Green_gap$_{ijt}$)	ln(L_{ijt-1})	ln(Internal_green_stock$_{ijt-1}$)	ln(Country_green_stock$_{ijt-1}$)	ln(Foreign_green_stock$_{ijt-1}$)	ln(Internal_non_green_stock$_{ijt-1}$)	ln(Country_non_green_stock$_{ijt-1}$)
ln(L_{ijt-1})	-0.3362						
ln(Internal_green_stock$_{ijt-1}$)	-0.0178	0.4832					
ln(Country_green_stock$_{ijt-1}$)	-0.2514	0.3518	0.6175				
ln(Foreign_green_stock$_{ijt-1}$)	0.5386	0.1859	0.7782	0.3243			
ln(Internal_non_green_stock$_{ijt-1}$)	0.0116	0.5183	0.8758	0.7485	0.7101		
ln(Country_non_green_stock$_{ijt-1}$)	-0.2424	0.3795	0.6231	0.9863	0.3356	0.7555	
ln(Foreign_non_green_stock$_{ijt-1}$)	0.5028	0.1233	0.6943	0.4051	0.9053	0.7729	0.4083

Table A.2: Tests of Unit Roots for patent variables (p-values)

	Levin et al. (2002)	Im et al. (2003)	Pesaran (2007)
ln(Green_gap$_{ijt}$)	0.00		0.00
ln(Internal_green_stock$_{ijt}$)	0.00		0.00
ln(Internal_non_green_stock$_{ijt}$)	0.00	0.00	0.00
ln(Country_green_stock$_{ijt}$)	0.00	0.00	0.00
ln(Country_non_green_stock$_{ijt}$)	0.00	0.00	0.00
ln(Foreign_green_stock$_{ijt}$)	0.00	0.00	0.00
ln(Foreign_non_green_stock$_{ijt}$)	0.00	0.00	0.00

Notes: All three tests investigate null hypotheses of non-stationarity (against the alternative of stationarity); test statistics in column 1 and 2 are based on the Stata xtunitroot (llc and ips, respectively) command, statistics in column 3 are based on the Stata pescadf command with a lag length of 1. No test results were reported for the two variables ln(Green_gap) and ln(Internal_green_stock) when employing the test by Im et al. (2003).

Table A.3: Testing the impact on the number of green inventions

	OLS log linear fixed effects regression
	ln(Green_inventions$_{ijt}$)
ln(L$_{ijt-1}$)	.07104
	(.0461)
ln(Internal_green_stock$_{ijt-1}$)	.67564***
	(.02397)
ln(Country_green_stock$_{ijt-1}$)	.13436**
	(.05435)
ln(Foreign_green_stock$_{ijt-1}$)	.12218***
	(.03276)
ln(Internal_non_green_stock$_{ijt-1}$)	.02007
	(.02914)
ln(Country_non_green_stock$_{ijt-1}$)	-.24645***
	(.06388)
ln(Foreign_non_green_stock$_{ijt-1}$)	-.06157
	(.08291)
Constant$_{ijt}$	.14961
	(.70593)
Year fixed effects	yes
Country-specific industry fixed effects	yes
N	6818
Groups	262
F	99.79***
R^2 within	0.72
Rho	0.34

Notes: see Table 3 for the variable definitions; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; i, industry; j, country; t, time.

Table A.4: Checking for outliers

	(1)	(2)
	OLS log linear fixed effects regression	
	$\ln(Green\_gap_{ijt})$	
	drop top 1%	drop top 5%
$\ln(L_{ijt-1})$	.26038***	.25403***
	(.06393)	(.06414)
$\ln(Internal\_green\_stock_{ijt-1})$	-.43714***	-.38696***
	(.02867)	(.02898)
$\ln(Country\_green\_stock_{ijt-1})$	-.24723***	-.15737***
	(.06374)	(.05736)
$\ln(Foreign\_green\_stock_{ijt-1})$	.37989***	.40029***
	(.04656)	(.0466)
$\ln(Internal\_non\_green\_stock_{ijt-1})$	-.00142	-.03118
	(.04434)	(.04387)
$\ln(Country\_non\_green\_stock_{ijt-1})$	.28851***	.20946***
	(.0833)	(.0785)
$\ln(Foreign\_non\_green\_stock_{ijt-1})$	.35351***	.39844***
	(.09597)	(.09382)
$Constant_{ijt}$	-5.312***	-5.3213***
	(.89507)	(.88989)
Year fixed effects	yes	yes
Country-specific industry fixed effects	yes	yes
N	6702	6341
Groups	258	244
F	42.33***	42.06***
R^2 within	0.40	0.41
Rho	0.71	0.68

Notes: see Table 3 for the variable definitions; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; i, industry; j, country; t, time.